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Automatically Generating Empirical Speed-Flow Traffic Parameters from Archived Sensor Data

Huan Li*

Mygistics Inc.,9755 SW Barnes Road Suite 550, Portland OR 97225, USA

Abstract

Traffic parameters used in the prediction models, which is traditionally based on assumptions, is one of the error sources for prediction. With the availability of traffic data in nowadays, the traffic data is popularly considered to apply for the validation of demand models. It is a crucial step for convincing the model prediction results. The flow-density model, which provides relationships between traffic flow variables, is a well-established approach for traffic prediction. Robust implementations of long-range planning and microsimulation models require calibration and validation of facility and time-dependent parameters (e.g. free flow speed, capacity, wave speed, critical density) which are sensitive to infrastructure, weather and other external factors. Archived data from freeway sensors provide a large sample from which to calibrate these parameters. In this paper, a set of automated traffic state identification tool is developed and applied to historical data to automatically determine the traffic phases. Once the traffic phase is known, we then calibrate the flow-density parameters with the fundamental diagram. Using this tool, with the identified traffic state for many days' data, the traffic parameters for free flow state and congestion state can be calibrated automatically in a fundamental diagram. As a case study, the calibrated traffic parameters in a dynamic traffic model (Cell Transmission Model) CTM are presented. The main findings of this paper is that an automated parameter calibration method is applicable for practical use, and this method provides a convincing result.

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Keywords: Freeway operation;fundamental diagram;traffic parameters;congestion identification;automation

* Corresponding author. Tel.:+1-503-575-2191.
E-mail address: hli@mygistics.com.

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1. Introduction

An automated approach for generating traffic flow parameters from various traffic data has drawn arising attention from many modelers as well as ITS practioners. With various types of traffic data available in nowadays, the validation of the traditional demand model using these traffic data becomes more and more important. There are many applications of traffic data in demand modeling, for instance, generating OD matrices, correcting traffic assignment and modifying traffic parameters in the flow-density relationship. In this paper, an automated tool for generating traffic parameters is presented, which can be applied for both off line and on line traffic prediction. It is mainly used for modifying the estimated flow-density relationship in demand modeling for both long term and short term traffic predictions. Especially, the benefit of this tool is more obvious for online traffic prediction. With an online data feed, the time dependent parameters can be generated automatically, and then, feed into the system directly.

The flow-density model, which provides relationships between traffic flow variables, is a well-established approach for traffic prediction. Robust implementations of long-range planning and microsimulation models require calibration and validation of facility and time-dependent parameters (e.g. free flow speed, capacity, wave speed, critical density) which are sensitive to infrastructure, weather and other external factors. Archived data from freeway sensors provide a large sample from which to calibrate these parameters. It is desirable that the calibration methodology is computationally efficient and suitable for use in real-time traffic monitoring and control applications.

When analyzing large amounts of archived data in an automated manner, it is critical to be able to accurately detect traffic breakdowns in time series while screening out random errors that falsely identify traffic breakdowns, as well as data quality and its resolution. In the literature, there are number of popular algorithms for tracking congestion systemically, such as Chen and Zhang's algorithm. The random detection errors are filtered arbitrarily by a moving horizon which checks the continuity of the detected 'congested' data points in a defined time period. The Automatische Staudynamikanalyse: Automatic Tracking of Moving Traffic Jams/ Forecasting of Traffic Objects (ASDA/FOTO) models (Kerner et al., 2004) uses a fuzzy inference system instead for the treatment of data. It serves for the further determination of traffic phases in its models. The rescaled cumulative tool proposed by Bertini and Cassidy is another widely used technique for traffic characteristics analysis. It exaggerates the trends of traffic flow changes, facilitates the detection of traffic breakdowns without concerning random error captions induced by the data resolution. This data transformation technique makes the detection of traffic breakdowns but requiring manual interpretation of graphical data. After the detection of traffic breakdowns, the traffic states need be determined. The key factors in this part are the chosen traffic variables, flow, speed or density, and the values of their thresholds which is sensitive to travel behaviors on the tested sites. Chen's method uses speed threshold and speed drop as indicators, totally two rules; and the ASDA/FOTO models, which not only looks at the speed, but also the flow, and their changes (in total thirteen rules). There are other similar method, such as Zhang and Levinson which uses occupancy differentials.

In our previous research (Li and Bertini, 2011), we developed an algorithm to detect traffic breakdowns based on Bertini and Cassidy method and compared several methods for the determination of traffic states. In this paper, we employ the previous algorithm for identifying traffic breakdowns and use the ASDA/FOTO model to further classify traffic phases. The remainder of the paper is organized as follows. First, we describe the freeway corridor and sensor data used in the development of our algorithm. We then describe the automated traffic state identification tool which is applied to historical data to automatically determine the traffic phases. Once the traffic phase is known, we then calibrate the flow-density parameters with the fundamental diagram. Using this tool, with the identified traffic state for many days' data, the traffic parameters for free flow state and congestion state can be calibrated automatically in a fundamental diagram. Then we show the application of the calibrated traffic parameters in a dynamic traffic model (Cell Transmission Model) CTM is presented. Finally, we present conclusions.

2. Site Description And Data

The freeway corridor selected for this analysis is southbound Oregon Route 217 (OR-217). As shown in Fig. 1, OR-217 SB is a 7-mile corridor that serves commuters during peak periods between downtown Portland and suburban areas in Beaverton, Tigard, Lake Oswego, etc. This freeway corridor contains 12 on-ramps, 10 of which are controlled by ramp meters since early November 2005. The locations of loop detectors are 0.75 miles apart on average (minimum of 0.31 miles and maximum of 1.23 miles). On-ramps also have detection but not off-ramps. A schematic of the highway showing the number of lanes, and the approximate location of detectors are shown in Fig. 1. Congestion occurs both in the morning and afternoon peak periods, with afternoons being more severe.

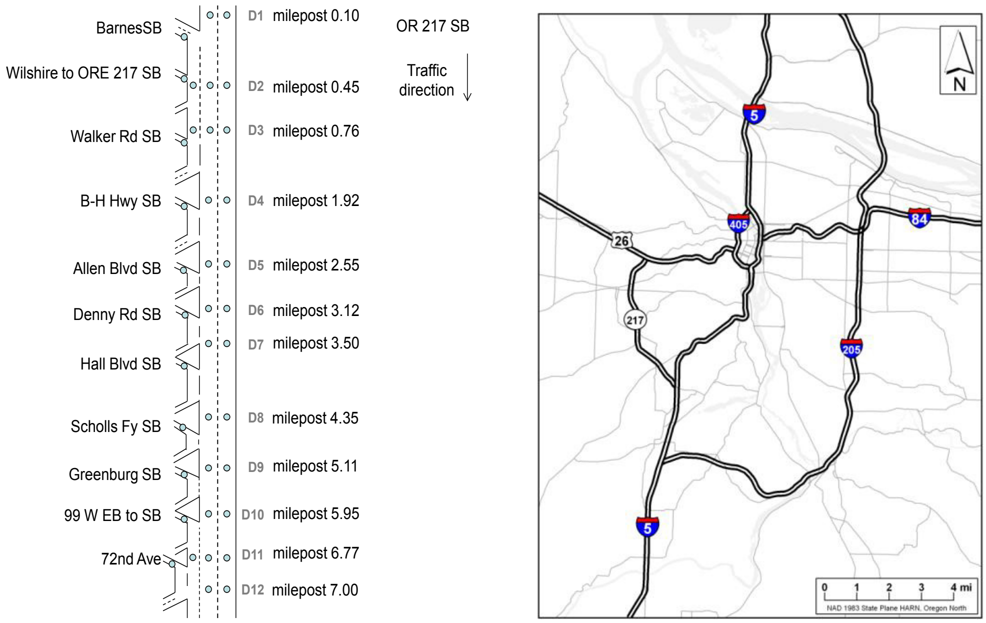


Fig. 1. Freeway Corridor Schematic (Not to Scale)

The traffic sensor data used in this analysis were obtained from the Portland Oregon Regional Transportation Archive Listing (PORTAL) data archive. For this analysis, count, speed and occupancy data at the lowest available resolution of 20 seconds for each day, including count, occupancy and time mean speed in each lane and on-ramp.

As mentioned above, the parameters for describing flow-density relationships is sensitive for various external conditions, including data fidelity, weather, occurrence of special events, and incidents. The occurrence of congestion is necessary in the analyzed days to provide sufficient samples for the congested traffic state. To develop our research data, we considered data from year 2007 to 2009 (1,095 days of data, archived in PORTAL). Data were filtered for weekdays, presence of congestion, presence of incidents, and data quality. The Besides the daily flow, speed and occupancy traffic data, PORTAL also provides other information including the incident location, time and duration, and data quality. The final dataset consisted of 27 days of data. A summary of the data filtering process is shown in Fig. 2.

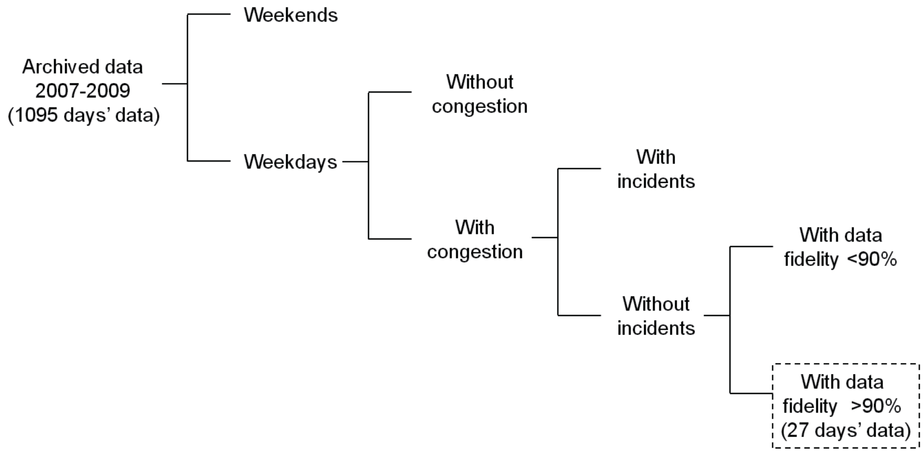


Fig. 2. Data selection

3. Methodology

In this section, we describe the automated techniques to process 27 days of 20-second detector data from OR-217 in order to estimate traffic parameters (e.g. free flow speed, wave speed, capacity, critical density, and jam density) at the station level.

3.1. Identification of Traffic Breakdowns

In previous work (Li and Bertini, 2011), we described the development of an algorithm to automatically identify traffic breakdowns using rescaled cumulative plots of measured traffic data. For clarity and context, we present an abbreviated description of the method. The reader is referred to (Li and Bertini, 2011) for more detail. The rescaled cumulative curve methodology proposed by Bertini and Cassidy is a data treatment technique, which exaggerates the changes of the cumulative count curves. This technique produces an oblique plot instead of the standard time-series plots. The oblique value can be explained as the deviation from the mean, which can be used to interpolate lines of constant slope representing stationary traffic conditions. Based on this method, our previous work used linear regression to perform piece-wise linear approximations to the oblique curve. The maximum and minimum oblique values in a determined time window were firstly considered as the candidates of traffic breakdowns. The curve can be truncated into three segments. For each segment, linear regression is performed to evaluate the reasonability of linear approximation, using the R^2 value to indicate curve fit. If the R^2 threshold is not met, new breakpoints within the segment are created from the segment's rescaled oblique values. The process is repeated for each segment until R^2 meets the condition to stop iteration, or the maximum number of iterations is reached.

To demonstrate, the automatically generated rescaled curves with the corresponding flow-density plots for milepost 2.55 from 3:30-6:30pm on November 19th, 2008 are shown in Fig. 3. The plots on the left side show the results of stationary segment identification by the automated tool; rescaled cumulative flow, speed and occupancy curves with superimposed line segments estimated by the regression. The mean value (from the algorithm) is labeled on each segment. The fundamental diagrams on the right side plot flow versus occupancy with a 2 min. aggregation level. The points in the fundamental diagrams are conditioned by color and symbol using the mean value estimated by the regression fitting. For example, in the second fundamental diagram the blue dots are 2 min. aggregated data points falling in the segment with a mean speed of 55 miles per hour, seen in the plot to the left. In the three plots on the right of Fig. 3, with few exceptions the fundamental diagrams have clear separations between congested and uncongested regions when identifying segments by speed or occupancy. The data points in the segment labeled as 55 miles per hour around 14:00 to 15:20 fall in the uncongested regime on the fundamental diagram, which is before the active congestion. Similarly, the data points in the segment labeled as 57 miles per hour around 18:40 to 20:00 fall in the uncongested region as well, which is after congestion recovery.

For the flow-defined segments there is also a clear separation, except for the segment with a mean value of 1,798 vehicles per hour. Similar results were observed for other days tested. One reason could be the presence of traffic in more than one state during the time aggregation or unstable flows during traffic state transitions, as flow does not clearly relate to the level of congestion. This effect is also observed at freeway bottlenecks (Cassidy and Bertini, 1999), where the sequences of low and high discharge rates immediately following queue formation vary in magnitude and duration. In this manner, we processed all of the archived data to determine congested and uncongested states.

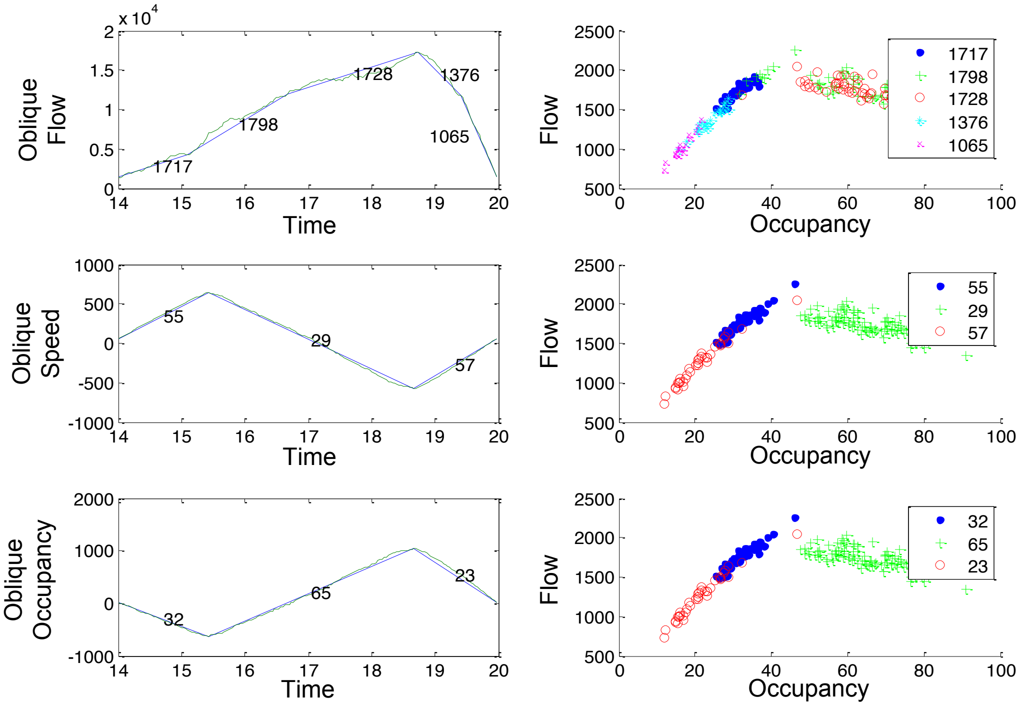
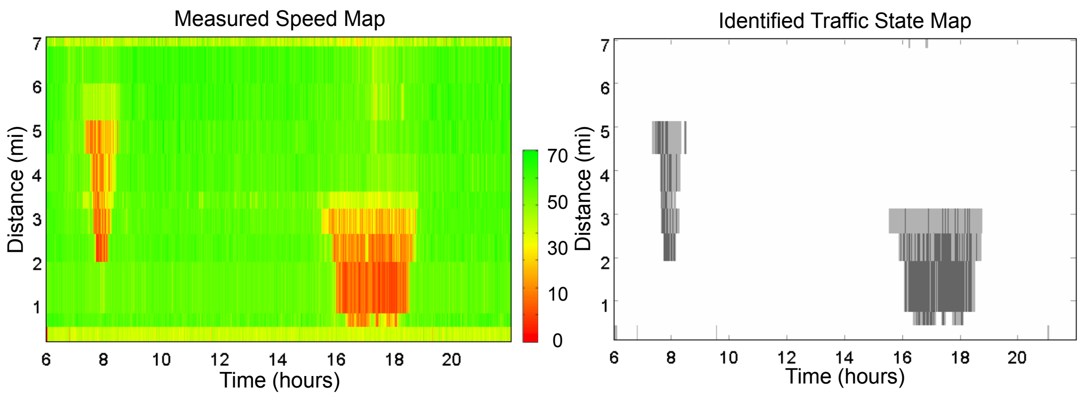


Fig. 3. Automatically generated rescaled curves and occupancy flow plots (2 min aggregation), 3:30-6:30pm, OR-217 SB milepost 2.55 on November 19th, 2008

Among the three traffic variables, vehicle speed and occupancy are stronger indicators of traffic state; flow is often used as an additional parameter to explore traffic phases. Traffic states can be automatically identified using a process described below that incorporates flow, speed and occupancy thresholds. We proceed to use threshold-based algorithms to further refine the congested and uncongested regimes. In previous research (Li and Bertini, 2011), two groups of rules compared in determining the traffic states, speed threshold rule and ASDA/FOTO rule. Through a statistical evaluation, the value of speed threshold was also tested as 35 mph and 15 mph speed differential (Bertini et al., 2008) for identifying the congested state in Portland region. The result showed that the speed threshold rule can efficiently and accurately identify congested traffic state from uncongested state. However, the speed threshold technique is not able to provide the detail within the congested traffic state. ASDA/FOTO, which is developed on three phase traffic theory, is famous for identifying the detail in congested state (Kerner et al., 2004). These traffic phases, free flow, synchronized flow or moving jam, are important for trip time estimation and prediction. In this circumstance, when the third phase synchronized flow is needed for application, ASDA/FOTO rule could be applied especially for identifying synchronized flow within the identified congested traffic state.

The automated recognition of traffic states was performed on OR-217 southbound traffic on November 19th, 2008. As mentioned, the data is processed station by station, through the automated rescale cumulative tool to identify traffic breakdowns. Then, the traffic state is determined through the classification of identified traffic phases by speed threshold rules. The result is shown in Fig. 4(b) that the area with white color is identified as uncongested traffic state, and the rest of the area is the congested traffic state. In order to learn the detail of congested state, the ASDA/FOTO rule is applied on the identified congested state without using any type of data transformation as the third step. The area with light gray color is recognized as synchronized flow. The dark gray area is the moving jam defined by ASDA/FOTO.

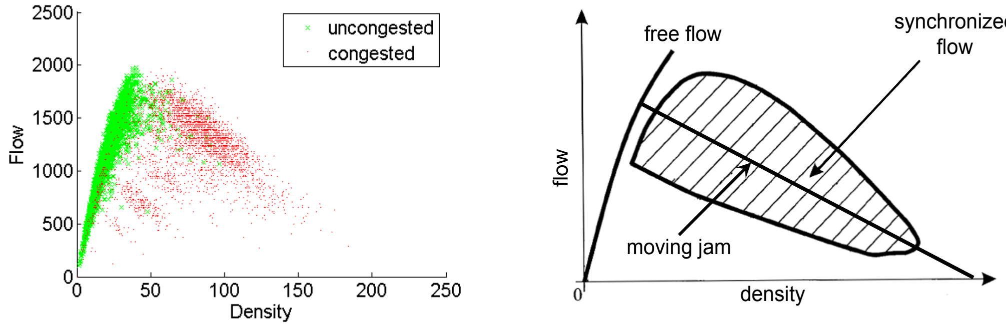


(a) (b)

Fig. 4. (a) Measured traffic speeds; (b) Automatically identified traffic states for OR-217 SB on November 19th, 2008

The flow density relationship for a single station over many days in history is also plotted in fundamental diagram in Fig. 5(a) which shows 27 days' data for southbound OR-217 at milepost 1.92 in Portland, OR. As shown in Fig. 5(a), the cross signs are data points identified as the uncongested state, and the dot signs are those identified as the congested state. The congested and uncongested region is clearly separated.

Historically there have been many proposed shapes for the flow-density/occupancy diagram. A recent flow-density/occupancy shape is proposed by Kerner as shown in Fig. 5(b). He proposes two different traffic phases in congested traffic: synchronized flow which is a two-dimension shape, and wide moving jams which is a straight line crossing over the synchronized flow area. It can be seen that the shape of the flow/density relationship is similar to Kerner's shape. The data points in the congested state are spread out as a two dimension shape, which is known as synchronized flow according his theory.



(a) (b)

Fig. 5. Results of automated classification of 27 days of [2-min] flow-density data, OR-217 SB at milepost 1.92

3.2. Calibration of traffic parameters

After identifying the traffic state, the traffic data for each traffic state can be collected over many days for supporting the calibration of the parameters on the fundamental diagram using regression analysis. Dervisoglu et al.

(2009) developed an automated calibration of traffic parameters using a mathematical method. However, the traffic states were simply truncated by the estimated critical density. Instead, in this research, they are determined by a theoretical definition of traffic state. With a large amount of data points accumulated in each region the free flow speed, queue propagation, and capacity can be estimated.

(1) Calibration of free flow speed

In Fig. 6(a), each data point with the cross sign represents an observed flow-density pair identified to be in free flow state. The shape slightly shows a second order polynomial model. However, for simplicity, a linear regression is performed instead to fit on the flow-density data points which are aggregated at the 2 min. level. The free flow speed is estimated to be 55.5 mph, shown as a solid line in Fig. 6(a).

(2) Calibration of queue propagation speed

Similarly, each data point with the dot sign in Fig. 6(b) represents an observed flow-density pair identified to be in congested state. The slope of the moving jam which is represented as a straight line crossing over the synchronized flow area is estimated. The regression used here is across all the data points in the congested states including both synchronized flow and moving jam. An estimate of certain quantiles of a population is required to find the straight line. The quantile regression is used when an estimate of the various quantiles (such as the median) of a population is desired, and it is robust in response to large outliers. It can be seen as a natural analogue in regression analysis to the practice of using different measures of central tendency and statistical dispersion to obtain a more comprehensive and robust analysis. This method, adopted by Dervisoglu et al. (2009) with the 75th percentile of the data points, is also used here to estimate the congestion speed. The solid line in Fig. 6(b) represents the queue propagation speed which has a value of 12 mph.

(3) Estimation of non-bottleneck capacity

Capacity is another important parameter to form a simplified fundamental diagram. According to the Highway Capacity Manual, capacity is defined as the maximum amount of flow that can reasonably be expected to traverse the cross-section of a road segment (2000 Highway Capacity Manual, 2000). The non-bottleneck capacity is estimated by examining the maximum flow in uncongested traffic state that can possibly go through the measured location based on historical data. For the purpose of model calibration, deterministic capacity estimation is implemented. The detected maximum flow over 27 days' data at milepost 1.92 on OR-217 is adopted as the capacity which is 1998 vehicle per hour per lane. The value is horizontally projected crossing the free flow speed line in Fig. 6(c). The crossing point represents the critical density, here 35.7 vehicles per mile.

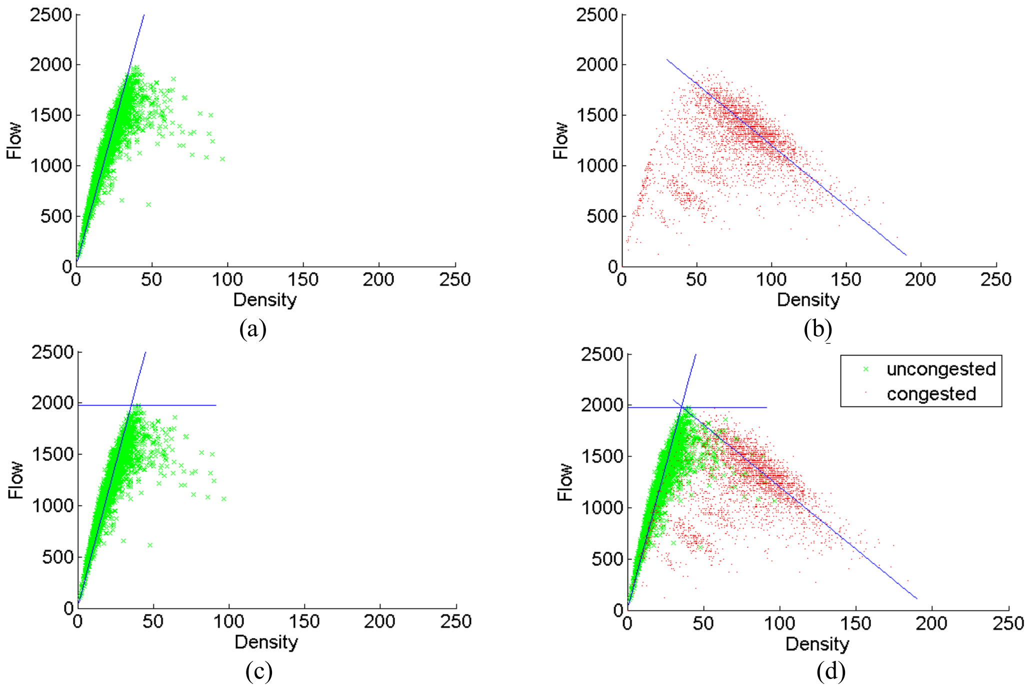


Fig. 6. Graphical estimation of traffic parameters, 27 days of [2-min] flow-density data, OR-217 SB at MP 1.92
(a) free flow speed; (b) queue propagation speed; (c) capacity; (d) estimated triangular diagram

4. Results

The methods described above are repeated for every detector station for input of the flow-density models. The results of this effort are presented in Table 1. The table shows that the estimated parameters vary by station. These values will be applied to a flow-density model for testing the effectiveness in the following section.

Table 1. Summary of traffic flow parameters for OR-217SB

Detector Name	Milepost	Free Flow speed (mph)	Wave Speed (mph)	Capacity (veh./hr/lane)	Critical Density (veh./mi)	Jam Density (veh./mi)
D1*	MP 0.10	42.3	-	1794	-	-
D2	MP 0.45	40.0	8.3	1800	45.0	262.4
D3	MP 0.76	40.0	10.2	1826	45.7	224.5
D4	MP 1.92	59.5	12.8	1998	33.6	189.7
D5	MP 2.55	59.9	16.5	2171	36.2	167.8
D6	MP 3.12	57.4	17.3	1737	30.3	130.7
D7	MP 3.5	60.2	12.0	2048	34.0	204.7
D8	MP 4.35	57.0	12.0	2255	39.6	227.5
D9	MP 5.11	52.2	7.8	2505	48.0	369.1
D10	MP 5.95	52.8	14.7	2475	46.9	215.2
D11	MP 6.77	49.7	15.3	1710	34.4	146.2
D12	MP 7.00	50.0	7.4	1800	36.0	279.2

*Note: Detector D1 has no observations on congested traffic state, the values of wave speed can only be obtained by assumption.

5. Application

We demonstrate the usefulness of estimating these traffic parameters empirically and automatically from archived sensor networks by incorporating them in a Cell Transmission Model (CTM) proposed by Daganzo. The CTM reproduces traffic phenomena in time and space and was chosen for its simplicity and dynamic representation of traffic flow. The case study uses a subset of the entire OR-217 highway for one particular day (November 19th, 2008). The model is simulated and compared to the actual measured values. The traffic state is determined by the inflow and outflow at each cell for every time step. It can not only simulate traffic congestion locations, but also congestion activation time and duration, as well as other traffic phenomena like merging and diverging, and queue propagation. The model was coded in Matlab for simulation and estimation. The important inputs of CTM include (Munoz et al., 2006):

- Freeway geometry;
- Boundary traffic flows, including on-ramp/off-ramp flow and in/out flow, which are raw data from detectors;
- Traffic flow parameters in the fundamental diagram, which were automatically calculated using the previous stated procedure (see, Table 2).

The evening peak hour traffic, which frequently has heavy congestion, was selected for the simulation. The simulated segment is from milepost 0.45 to milepost 4.35, 3.9 miles long in total. The detector stations are marked as circle dots in Fig. 7.

For modeling, the segment is partitioned into 12 cells, with increasing index in the direction of traffic. It is essentially divided at each on-ramp and -ramp location. The cell length must meet the requirement of CTM that it should be longer than the free-flow travel off distance: that is, for each time step T_s, with the free flow speed V_i for cell i:

$$V_i T_s \le l_i \tag{1}$$

Where l_i is the cell length.

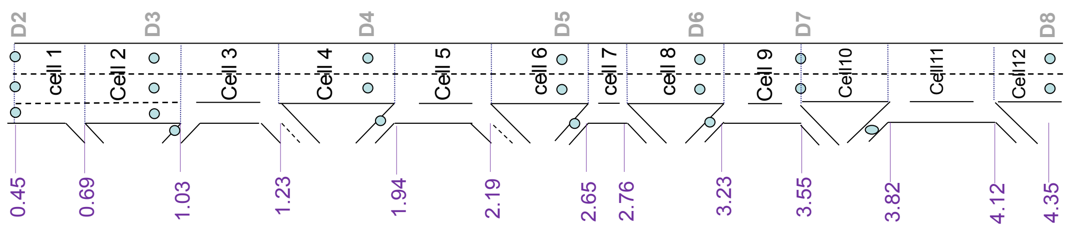


Fig. 7. Definition of Cells and Geometry for CTM, OR-217SB, MP 0.45 to 4.35

5.1. Boundary Traffic Flows

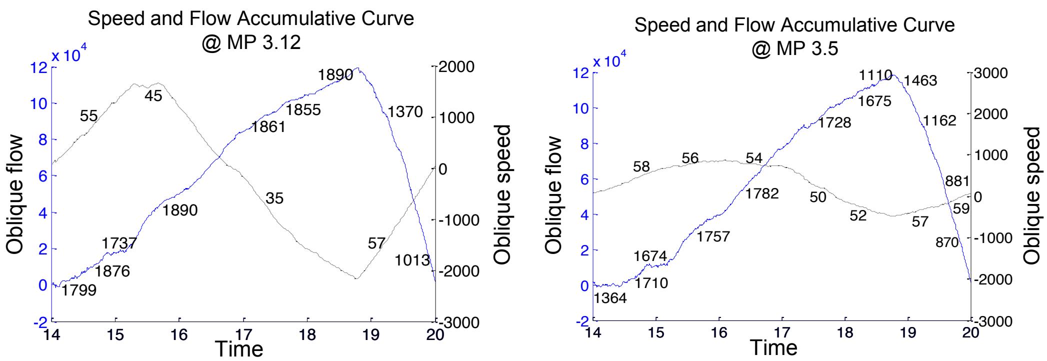
A complete demand dataset consists of the measured flow at upstream mainline boundary at detector D2, along with the flows at each on-ramp and off-ramp, over the period 2PM-8PM for the selected day, November 19th, 2008. As shown in Fig. 7, the deployment of detectors (shown as circled dots) in Portland considers the conservation of traffic flow on freeways. The on-ramp flows are measured data, and the off ramp flows are calculated from the sum of upstream mainline and on-ramp flows minus the downstream mainline flow. The time offset of off-ramp flow is ignored since the travel time between detectors, which is less than 1 min, is comparatively short when using 5 min aggregated data as the input.

5.2. Traffic Flow Parameters

The automated calibration of traffic parameters is applied to 27 days' archived data for southbound OR-217. Every selected day exhibits congestion on the simulated segment and is incident free. The parameters free flow speed and queue propagation speed are calculated for all the stations in this segment using the regression analysis. The capacity at the bottleneck location is measured using the automated cumulative curve tool. The nominal capacity at non-bottleneck locations must be chosen to be larger than the maximum observed flows. The maximum flows at non-bottleneck locations are first observed in history, and then these values are adjusted higher if the observed maximum flow is less than 1800 vehicle per hour. The critical density and jam density are calculated based on a triangular shape of flow density relationship. The parameters at these 7 detector stations are listed in Table 1. Then, the parameters of the cells without detectors are assigned using the adjacent detector parameters.

5.3. Bottleneck Capacity

While bottleneck location detection and its capacity were not automated in our algorithm, they are nonetheless important traffic information. We estimate the bottleneck capacity manually for this particular day. As shown in Fig. 8(a), the bottleneck is located between the detector at milepost 3.12 and the detector at milepost 3.5 on the analyzed day. Bottleneck location is automatically detected from the cumulative traffic flow and speed curve for the paired-detector stations in Fig. 8, by recognizing that the upstream station milepost 3.12 has a speed drop with an increase of flow, and the downstream station milepost 3.5 has a free flow state.



(a) (b)

Fig. 8. Identification of Bottleneck with Rescaled Cumulative Curves, OR-217 SB on November 19th, 2008

After examination of the bottleneck location, the bottleneck capacity can be estimated by looking at the downstream discharge rate. Traffic in an active bottleneck exhibits nearly stationary patterns with discharge flows that alternate between higher and lower rates. In particular, a period of rather low discharge flow, followed by a period of relatively high flow, always accompanies the onset of upstream queues (Cassidy et al.,1999). The maximum flow at milepost 3.12, which is upstream of the bottleneck location, is around 1737 vehicle per hour per lane before the bottleneck is active at around 15:20 pm, see Fig 8(a). At the same time, the discharge rate downstream of the bottleneck location at milepost 3.5 is around 1750 vehicles per hour after the bottleneck is activated, which is very close to 1737 vehicle per hour.

5.4. Results

Fig. 9 shows the time space plots for the measured and simulated densities and flows for all lanes on the OR-217 test segment during the afternoon hours. The effect of flow-density hysteresis is approximated knowing parameters in the model. Knowing the bottleneck location and capacity, the congestion propagation can be assessed and simulated - the queue formation and recovery is closely simulated.

The distinct difference between measured and simulated data is the variance. In Fig. 9, the presented measured data are raw flow and density with 20 sec resolution. The traffic flow and density is simulated at each 10 Sec time step with the use of the dynamic equation in the CTM. The higher the resolution of measured data, the lower variance However, the simulated data has a small variance for the reason that the demand data are aggregated at 5 min resolution, which has a small variance. The simulation was run for 10 sec time steps, using the same 5 min input demand for 30 time steps, then switching to the next data. A large variance data input may impact the accuracy of the simulation. Further, spatially the simulation approximates the traffic state between detectors. When the traffic detectors are placed farther apart, as in some cities, this estimation discovers the traffic state between detectors, and thus making the travel time estimation more precise compared to the estimation based on the detector data.

The simulated and measured data are further compared at some single locations where the cells possess detectors referring to Fig. 7. The flows and densities for Cell 6 and Cell 8 are plotted in Fig. 10; but the measured data in this figure are 5 min aggregated data, which makes the trend clear. The density and flow are predicted similar to the measured values. For next step, the travel time and congestion activation and deactivation times can be predicted by using this model with the automated parameter calibration procedure.

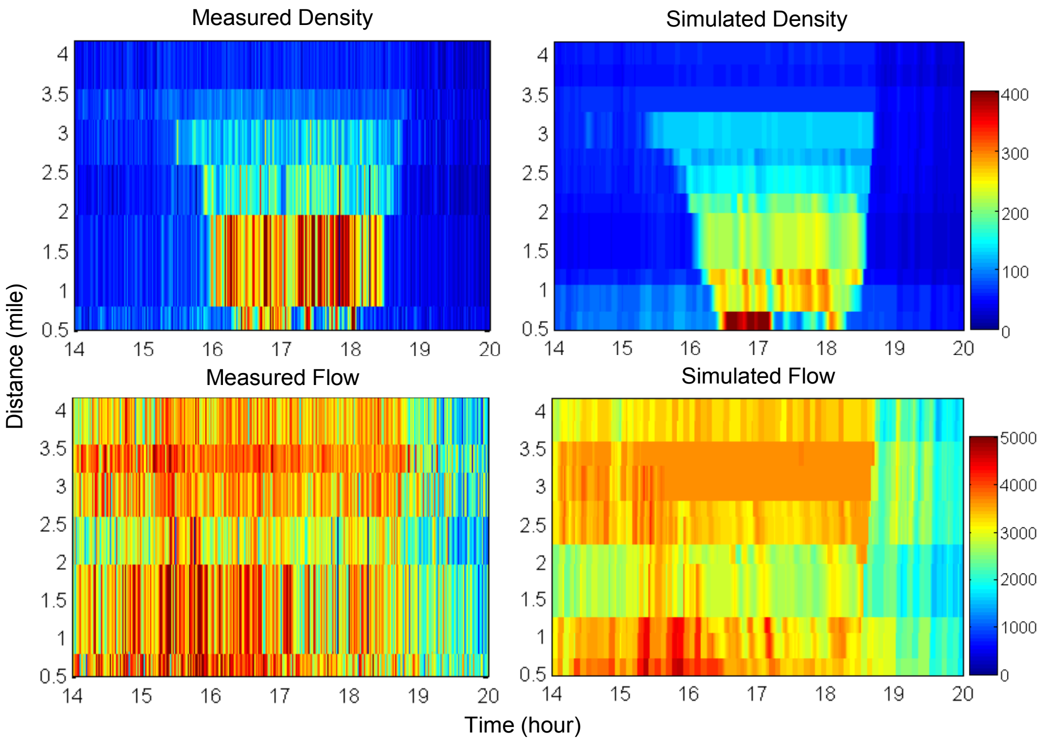


Fig. 9. Comparison of Measured and Simulated Data, OR-217 SB on November 19th, 2008

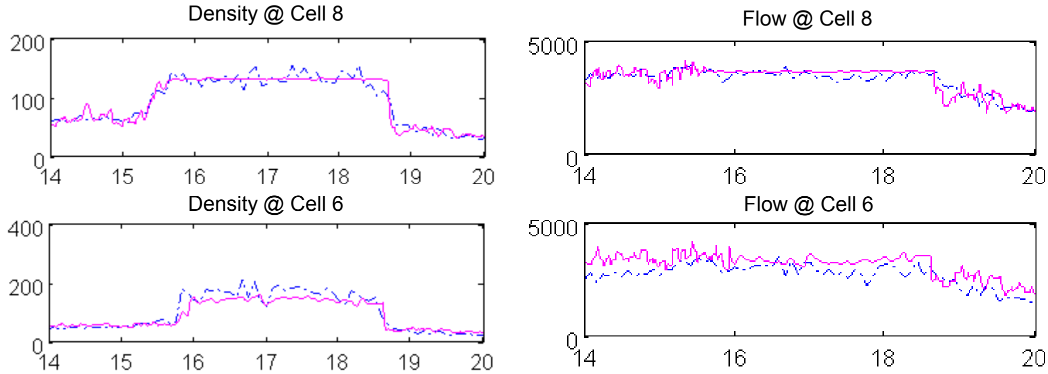


Fig. 10. Results of Cell 6 and Cell 8, OR-217 SB on November 19th, 2008

6. Conclusions

With the growing and ongoing collection of archived freeway sensor data at high-resolution, it is realistic to validate traffic models rather than relying on assumptions. Calibrating these parameters is data intensive and time consuming. In this paper, we present a fully-automated calibration of traffic parameters using the archived data. This tool facilitates the model validation process for both off line and on line traffic prediction. Using this tool, with the identified traffic state of many days' data, the traffic parameters for free flow state and congestion state can be calibrated automatically in a fundamental diagram. To demonstrate the usefulness a case study is presented as an application of this automated procedure on a dynamic traffic model CTM. The results that with well-calibrated parameters, the CTM model was able replicate real-world traffic conditions quite accurately. Through the case study, the result shows that this tool provides a convincing parameter calibration result and can be applied for practical use. Especially, when doing online traffic prediction, a time depended parameter can be calibrated through an online data feed. It facilitates the whole process of online prediction features.

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